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Demand Effects of Recent Changes in Prescription Drug Promotion

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"Advertisements contain the only truth to be relied on in a newspaper."
Thomas Jefferson

"Advertising is a racket . . . its constructive contribution to humanity is exactly minus zero."
F. Scott Fitzgerald[1]

"I think I was wrong . . . . On the whole, I think there is a lot of educational benefit" (to direct-to-consumer prescription drug advertising).
David A. Kessler, M.D., former FDA Commissioner[2]

Since 1994, total spending on consumer-directed promotion for prescription drugs has grown nearly tenfold [Henry J. Kaiser Family Foundation 2000]. Consumers and their physicians report that prescription drug advertisements are increasingly influential. In surveys of consumers, the share of people reporting they have seen an advertisement on television or heard an advertisement on the radio for a prescription drug more than doubled between 1993 and 2000, reaching 81% by 2002 [Alperstein and Peyrot 1993; NewsHour/Kaiser/HSPH 2000; Aikin 2002]. Some estimates indicate that as many as 25% of Americans have asked their doctors about a medication as a result of seeing an advertisement [Prevention Magazine, 2001]. Similarly, many physicians report that their patients have asked them about drugs as a direct consequence of consumer advertising [Borzo 1997; Kaufman and Hoffman 1997].

The rise of direct-to-consumer advertising (DTCA) of prescription drugs represents a departure from the industry's historical concentration on promotion to physicians, hospitals, and other health care organizations.[3] This phenomenon is highly targeted towards a minority of products. In one recent study of 391 major branded drugs in 1999, only 18% had positive DTCA expenditures, whereas 95% of brands sent "detailers" to visit physicians' offices [Neslin, 2001]. Traditional physician-oriented forms of promotion remain important. Even among those products that employ DTCA, professional promotion continues to command a larger share of marketing budgets [Table 2].

The change in marketing mix by pharmaceutical manufacturers is likely a response to recent changes in market and regulatory conditions.[4] Consumers are increasingly seeking active participation in their own health care, aided in part by the wealth of information available on the Internet. At the same time, physicians may have less discretion over choice of brand name drugs than they once did as a result of direct and indirect constraints placed on their prescribing behavior by managed care. In addition, in 1997 the FDA released tentative guidelines (finalized in 1999) regarding advertising to consumers via electronic media such as radio and TV. These guidelines may have facilitated more widespread use of these media. In particular, the new FDA guidelines clarified the requirements for adequate disclosure of information concerning indications, risks and effects of a drug, thus removing a major barrier to television and radio advertising [Rosenthal et al. 2002].

The release of updated FDA guidelines and independent changes in consumer behavior provide an opportunity to study the effects of DTCA in the prescription drug market as well as the effects of various physician-oriented promotions. In this paper, we examine the effects of two types of promotional spending for brands in five therapeutic classes of drugs, using monthly aggregate U.S. data from August 1996 through December 1999. Specifically, we provide evidence on two issues: (i) Do increases in DTCA increase the market size of an entire therapeutic class? (ii) Does relative DTCA within a given therapeutic class affect market shares within that therapeutic class? In both cases, we examine these impacts relative to traditional physician-oriented promotional efforts.

I. Review of Related Literature

Our research builds on and relates to a number of other studies. Early economic studies of physician-oriented marketing of prescription drugs by Bond and Lean [1977], Hurwitz and Caves [1988], Leffler [1981], and Vernon [1981] considered evidence that this marketing was more "persuasive" than "informative", although the distinction between the two was ambiguous. This distinction reflects a more general literature that viewed advertising alternatively as changing consumers' preferences [Kaldor 1950], creating or exaggerating product differentiation and thereby increasing barriers to entry [Bain 1956], or as providing information about a product's characteristics and its price [Stigler 1961]. A common finding from the empirical literature was that professional promotion of prescription drugs increased entry costs and decreased price competition by increasing perceived product differentiation. A related medical study on physician detailing is by Avorn, Chen and Hartley [1982], who advocated counter-detailing to offset the unbalanced information provided by prescription drug detailers.[5]

More recent research by King [2000] on anti-ulcer medications finds that own marketing reduces (in absolute value) a brand's own price elasticities of demand, but that total industry marketing reduces the extent of product differentiation. Berndt et al. [1997] distinguish between "industry expanding" and "rivalrous" marketing efforts, and find that for antiulcer medications cumulative spending on both medical journal and physician detailing increases own-brand sales. They also report that the impact of total class marketing efforts on total class sales is positive, and generally (but not always) declines with the number of products on the market. Rizzo [1999] reports that for antihypertensive drugs, both stocks and flows of detailing expenditures decrease the price elasticity through the development of greater brand loyalty.

Using a proprietary data set from a pharmaceutical manufacturer that incorporates physician-specific marketing measures for one of its brands, Manchanda, Chintagunta and

Gertzis [2000] find that detailing has a significant positive impact on the number of prescriptions written for that drug by the physician, that this marginal impact increases when free product samples are also provided to the physician, and that for the majority of physicians in their sample, diminishing (though still positive) returns to detailing had already set in. Gonul et al. [2001] report similar diminishing returns to physician detailing, but find that detailing and free samples increase price sensitivity, where price is measured as the average retail price for the drug.

The empirical studies cited above focused on physician detailing, and in some cases, medical journal advertising, but did not examine DTCA.[6] Unlike physician-oriented promotions, to the extent that DTCA raises awareness among previously untreated consumers of the existence of potentially effective treatments, DTCA could bring more patients into physician offices. Whether the effect of such increased "physician office foot traffic" is greater on overall therapeutic class sales, or on the share of sales for the specific brand named in the advertisement, is unclear a priori and is an empirical question addressed in this study.

Prior to 1997, DTCA was permitted if a medical condition was mentioned but the brand was not, or if the brand was mentioned, no mention was made of the medical condition for which it was intended, and instead the ad encouraged the individual to see her/his physician regarding the brand. Berndt et al. [1995] obtained ad agency DTCA data for branded antiulcer (H_2-antagonist) prescription drugs up through May 1994, along with detailing and medical journal advertising data from other sources. For the entire H_2 therapeutic class, advertising demand elasticities were 0.55 for detailing, 0.20 for medical journal advertising, and 0.01 for this type of DTCA; the sum of these elasticities is 0.76, suggesting decreasing returns to scale to overall advertising. Within this therapeutic class, although own-detailing and own-medical journal advertising stocks positively affected own-market shares, own DTCA had no significant impact on own-market share.

Two recent studies of DTCA by Wosinska [2001] and Ling, Berndt and Kyle [2002] incorporate data after the FDA's 1997 clarification of DTCA guidelines. Wosinska uses 1996-

1999 prescription drug claims data for 4,728 patients who filled a total of 11,529 new prescriptions for cholesterol reducing drugs in the Blue Shield of California medical plans, along with national data on physician detailing, samples and DTCA. She finds that DTCA positively impacts total therapeutic class sales, but only impacts an individual brand positively if that brand has a preferred status on the third party payer's formulary.

Unlike the cholesterol-reducing drugs, the H_2-antagonist drugs are sold not only in prescription (Rx) form, but since 1995-96 also as over-the-counter (OTC) drugs. Both OTC and Rx versions of these brands have utilized DTCA, and thus various spillovers between Rx and OTC DTCA can be assessed, both between and within brands. Ling, Berndt and Kyle find that DTCA marketing of OTC brands has no spillover to the same brand in the Rx market. Within the Rx market, own-brand physician-oriented detailing and medical journal advertising efforts have positive and long-lived impacts on own Rx market share, while DTCA of the Rx brand has no significant impact on own Rx market share. Within the OTC market, not only are own-brand impacts of DTCA on the OTC brand significantly positive and long-lived, but physician-oriented Rx marketing efforts have positive own-brand spillovers to the OTC share. DTCA efforts for Rx brands have no significant impact on same-brand OTC shares.

II. Theoretical Considerations

The codfish lays ten thousand eggs,
The homely hen lays one.
The codfish never cackles
To tell you what she's done.
And so we scorn the codfish,
While the humble hen we prize,
Which only goes to show you
That it pays to advertise.[7]

The theoretical foundations underlying the economics of advertising rely in large part on Dorfman and Steiner [1954], who showed that for a profit-maximizing monopolist facing a downward-sloping linear demand curve, the optimal advertising expenditure to dollar sales ratio equaled the ratio of two-elasticities, ε_{QA} -- the elasticity of quantity demanded with respect to advertising efforts, and ε_{QP} -- the elasticity of quantity demanded with respect to price (in absolute value), i.e.,

$$\$ \text{ Advertising}/\$ \text{ Sales} = \varepsilon_{QA}/\varepsilon_{QP}. \qquad (1)$$

The Dorfman-Steiner theorem is static in that it assumes that advertising efforts last only one time period, but it can readily be generalized to a dynamic case in which the effects of advertising efforts persist several periods into the future -- so-called "carryover" effects [Schmalensee 1972]. When there are several marketing instruments (and constant unit marketing media costs), under reasonable conditions the optimal ratio of expenditures for any two media equals the ratio of their marketing elasticities [Palda 1969].

In terms of demand marketing elasticities and advertising-sales ratios, it is useful to consider the taxonomy of Nelson [1970,1974], who has distinguished as polar opposites search and experience goods. If a consumer can determine a product's quality and impact prior to purchase merely by visual, tactile or analytical inspection, the product is said to have search qualities. Examples of search goods are many electronic goods, tools, and credit cards. If a customer must consume the product to predict its quality and impact, the good is said to have experience qualities. Examples of experience goods include cosmetics, restaurants and cereals. Although in practice precise demarcation of goods into search vs. experience is not possible, particularly when multi-attribute goods have both search and experience qualities, in general goods with dominant experience attributes have greater advertising-sales ratios than do goods with dominant search qualities. To the extent prescription pharmaceuticals have idiosyncratic and unpredictable impacts (differential efficacy, side effects and adverse interactions with other drugs), pharmaceuticals would appear to have more experience than search qualities. However, for those pharmaceuticals having highly predictable outcomes, search qualities may dominate.

Carlton-Perloff [1994] suggest that producers of search goods are more likely to use informational advertising, while experience goods producers are more likely to use persuasive advertising, although they note that the division is not perfect, nor is there unanimity in what constitutes information vs. persuasion. They interpret the greater advertising-sales ratios of experience goods as possibly reflecting the fact that "images (used in persuasive advertising) are forgotten more quickly than facts (used in informative advertising). Thus, consumers may learn and remember that a particular good has fewer calories (is "less filling") in one or a few exposures to an advertisement, but need to be bombarded with repeated exposures to be convinced that a product "tastes great"."[8]

The effects of advertising on the welfare of individuals have long been analyzed and debated. Carlton-Perloff summarize this literature by stating that "the welfare effects of advertising are complex and depend on the type of product and type of advertising", and therefore "are generally ambiguous".[9] Brand loyalty, for example, may reduce price responsiveness of demand, but can also reduce consumers' search costs.[10] Bagwell [2001] provides a useful collection of economics articles dealing with the theoretical foundations and empirical analyses of advertising as information vs. persuasion, search vs. experience, and the relationships among advertising, product quality and market structure.[11]

Finally, in addition to affecting demand, advertising can be used as a strategic tool to affect possible entry into a product market. Ellison and Ellison [2000] hypothesize and empirically assess branded pharmaceutical firms' advertising strategies in the context of affecting potential generic entry as the brand's patent protection expires. They find empirical evidence supporting their theoretical prediction that branded drugs with medium size markets reduce their advertising intensities to a greater extent prior to patent expiration than do drugs with either very small or very large markets.

III. The Marketing of Prescription Pharmaceuticals: Descriptive Data

Pharmaceutical companies currently employ a number of promotional strategies for prescription drugs designed to target professionals and consumers, respectively (Table 1). Because physicians have long been the key decision makers when it comes to choosing a prescription drug, pharmaceutical companies traditionally have concentrated most of their marketing efforts on physicians, and still do so today. These physician-oriented marketing efforts include visits or phone calls by pharmaceutical sales representatives to physicians (detailing), free samples, print advertising, and sponsorship of medical education events. In 2000, the vast majority of spending on professional promotion (about 81%) was concentrated on detailing (30.6%) and samples (50.6%).

Consumer-oriented promotion, which includes advertising in both print and electronic media, was nearly non-existent as an approach to promotion of pharmaceuticals in the U.S. as of 1980. Beginning in the 1980s and early 1990s a limited amount of DTCA began appearing. By 1994 a rapidly increasing trend in DTCA spending became apparent (Figure 1). The release of the clarified FDA guidelines in 1997 occurred in the midst of this trend and may have accelerated it. By 2000, DTCA comprised 15.7% of total promotion expenditures.[12]

As shown in Table 2, there is very substantial heterogeneity in DTCA and physician-oriented promotion to sales ratios. For new products, this ratio can be as high as 2.05 (Aciphex, a proton pump inhibitor), and as low as 0.0 (Mevacor, a cholesterol reducing drug). Within classes, there is also substantial heterogeneity in DTCA, detailing and sampling to dollar sales ratios (e.g., the antidepressants and nasal spray classes in Table 2).

IV. Empirical Implementation

Our aim is to estimate the impact of DTCA on consumer demand for prescription drugs. The literature on the demand for prescription drug products makes use of a number of approaches to model specification. These include implementation of Almost Ideal Demand System (AIDS), Cobb-Douglas specifications and logit models [Ellison et al. 1997; Rizzo 1999; King 2000; Ling, Berndt and Kyle 2002; Frank and Hartman 2002]. Each specification has its advocates in the literature. None has yet been shown to be superior in estimating demand models in markets for prescription drugs.

Following others, in the demand analysis pursued here we estimate the demand for prescription drug products in the context of multi-stage budgeting. That is, we estimate models of the impact of promotional spending (DTCA and detailing) at the level of the entire therapeutic class (e.g., Selective Serotonin Reuptake Inhibitors (SSRI) antidepressants) and at the level of the individual product within the class (e.g., Prozac among the SSRIs).[13] This multi-stage structure is illustrated in Figure 2. At the top level of the tree, which represents the therapeutic class of drugs, we estimate the impact of DTCA spending and detailing in the context of a Cobb-Douglas demand specification (double logarithmic). In the analysis of competition at the individual product level within each class we specify and estimate three alternative models: 1) an AIDS type specification; 2) a logit model with log of quantity share divided by (1- quantity share) on the left hand side, and prices and promotional spending on the -right hand side; and 3) a Cobb-Douglas model in log levels.

A. Data Sources

We examine monthly data from August 1996 to December 1999 for five therapeutic classes of drugs: recent vintage anti-depressants (SSRIs plus serotonin/norepinephrine reuptake inhibitors (SNRIs)), antihyperlipidemics, proton pump inhibitors, nasal sprays, and antihistamines (Table 2). These classes were selected on the basis of the following criteria: (1) presence of at least one product with high DTCA expenditures during the time period, (2) within class variation in DTCA, and (3) within class variation in the life cycles of the drugs. The classes treat a wide variety of ailments, are indicated for different patient populations and are prescribed by a number of different clinical specialties. Data were collected on all of the drugs in each of these five classes.

Sales and promotion data for selected products were obtained from marketing research firms. Data on DTCA spending were obtained from Competitive Media Reporting (formerly known as Leading National Advertisers), which tracks local and national advertising campaigns in major media such as television and radio for brands with at least $25,000 in annual advertising expenditures. Three major components of professional promotional spending are reported here: detailing to office-based physicians, detailing to hospital-based physicians, and the value of free samples left with physicians. Drug-specific data on professional journal advertising, which represents a small percentage of overall promotional expenditures for products in the six drug classes, was not included.

Spending data on detailing was obtained from Scott-Levin Inc., a pharmaceutical market research firm. Scott-Levin imputes spending on detailing from a panel of roughly 12,000 office- and hospital-based physicians, which comprises roughly two percent of the U.S. physician population. The physicians track their contacts with pharmaceutical sales representatives. Data on the retail value of free samples provided by pharmaceutical companies were obtained from IMS Health, which uses a panel of 1,265 front office staff in medical practices to monitor the volume of samples dropped off by sales representatives. We used the retail value of samples to approximate the opportunity cost to the pharmaceutical companies of giving away free samples. Because samples presumably crowd out at least some sales, production costs would understate the cost of samples to the manufacturers. Using the retail price to value all free samples probably overstates the opportunity cost to the manufacturer, however, so that our marketing elasticity for professional promotion may be underestimated. Sales data were obtained from Scott-Levin, which audits over 35,000 retail pharmacies and projects total sales based on an independent estimate of total U.S. retail sales of prescription drugs.

Market shares were constructed from product-level data on sales for the drugs in each of the six classes. Price data were constructed by Scott-Levin using their sales data. We then created a quantity sold variable based on dividing sales by price for a particular month. Note that this price variable is not the average consumer copayment for that drug, but instead is the average price received by wholesalers from their customers.

Patent information was collected from the Food and Drug Administration's *Orange Book.* A variable was created to indicate the number of months left on a product's patent. Order of entry within a class was determined based on the FDA approval date available through the *Orange Book.*

Table 2 identifies the therapeutic class and individual product combinations that are analyzed below. Together these five classes accounted for 30% of all DTCA in 1999. Table 2 also reports the year each drug was approved, the three-year average promotion to sales ratio for detailing, sampling and for DTCA.

B. Basic Models

We now set out the basic estimation models used in the analysis. As noted above, the Cobb-Douglas formulation is used for both the class level demand model as well as the individual product demand model. Equation (2) is the Cobb-Douglas specification for the product specific analyses:

$$\ln q = \alpha + \beta_1 \ln DTCA + \beta_2 \ln Det + \sum_j \delta_j X_j \qquad (2)$$

where Det is detailing and the X_j 's are other explanatory variables.

Equation (3) represents the general specification of the modified AIDS model.

$$S_i = \alpha + \beta_i \ln\left(\frac{P_i}{P_j}\right) + \phi_i \ln DTCA + \phi_2 \ln Det + \sum_{ix} \sigma_{ix} X_{ix} \ , \qquad (3)$$

where S_i is the dollar revenue share of the ith drug within a therapeutic class, and P_i and Pj are prices of drugs i and j (in our model, P_j is actually the share-weighted price index for other competitors in the class because there are more than two drugs in every class). Finally, we use the same right hand side variable in estimating model specifications where the dependent variable is specified as the logit of quantity shares for the individual drug products. Several variants of these specifications are also estimated as discussed below.

C. Specification and Measurement of Key Variables

There are two important sets of measurement and specification issues with our demand models of prescription drug promotion. They are: 1) the measurement and specification of the price variables, and 2) the specification of promotional spending. The appropriate price to measure in a traditional consumer demand model is the out-of pocket cost of the drug to the consumer. For a variety of reasons this desired measure is not available. The Scott-Levin data we analyze measures price as the payment made by drug stores to wholesalers for each drug. Because this measure takes into account discounts and charge-backs to pharmaceutical manufacturers, these prices are not simple list prices. Nevertheless, these observed prices do not take account of the rebates that are given to health plans and other third party payers for prescription drugs, nor the structure of beneficiary cost sharing for prescription drugs by health plans. Both the level of rebates obtained by different payers and the structure of co-payments are quite heterogeneous, even within the customers of a single drug store [Frank 2001]. Thus, the observed prices are measured with error and are probably not closely correlated with the desired consumer out of pocket price. For these reasons we take two approaches in empirical implementation. In one set of models we include the mismeasured price variables. In another set of models we omit the price variables and instead include a more extensive set of indicator variables to account for time trends and unobserved cross sectional effects.

The specification of measures of promotional spending has generally taken one of the three forms in the literature. Promotion has been treated as a simple flow variable that is measured by current levels of promotional spending [Wosinska 2001]. That approach assumes that current buying behavior depends largely on current exposure to promotional activities. A second approach specifies promotional activity as affecting consumer choice in terms of a lag structure [Rizzo 1999, Wosinka 2001]. The assumption here is that the appropriate measure is still viewed as a flow, only there is a lagged response to the promotional activities. The third approach is to treat promotional activity as a stock that depreciates at a constant rate over time [Berndt et al., 1995, 1997].

Our point of departure is to treat promotional spending as a simple flow. We also explored creating a stock. Our historical data on DTCA and detailing is, however, quite limited. We therefore experimented with a variable based on three-month cumulative spending. When we used this variable in the specifications, our time series was shortened, and the resulting parameter estimates did not differ markedly from those assuming a simple flow. We therefore chose to focus on the results that are based on treating promotional spending as a simple flow.

We take account of the possibility that spending on DTCA and physician promotion and product sales are jointly determined by estimating instrumental variables (IV) models where all three variables are assumed to be endogenous. Three sets of variables serve as the basis for our exclusion restrictions in the IV specifications for the product specific demand equations. The first is the time left on patent for each drug (and its square). This is based on the notion that for products reaching the end of their patent protection period there is little incentive to invest in promotion [Frank and Salkever 1992; Berndt, Kyle and Ling 2002]. The length of the patent life remaining is determined far in advance of current sales decisions, and there is no direct effect on sales because there is no generic competition for these drugs yet in place. The second instrument reflects the timing of the FDA's clarification of the conditions governing direct-to-consumer advertising on television (and the interaction of that indicator with time). In 1997 the FDA clarified that television advertisements could refer consumers to a physician, a 1-800 number, a manufacturer web site and a magazine article that provides the full description of the drugs as required by labeling regulations. This clarification served to reduce the cost of airing a television promotional spot but should not have had a direct impact on sales. The third instrument is the interpolated monthly value of television advertising costs per minute, based on annual data from Robert M. Coen Associates.

The IV model for DTCA is estimated using a two-part model where the first stage is a logit of whether there was any spending on DTCA in a given month and the second stage is a regression model on the natural log of DTCA conditional on any spending (Cragg 1971; Duan et al. 1983). For detailing a simple two-stage IV was estimated because all drugs in the sample were promoted via detailing.

Finally, we experiment with several specifications of a time effect. We use a combination of quarterly dummy variables to capture seasonal effects, and a quadratic time trend to account for secular trends in the pharmaceutical marketplace. All models estimate standard errors robust to heteroskedasticity and clustering.

VI. Econometric Results

We begin by presenting results in Table 3 for the top of the tree structure in Figure 2, the class level quantity equations. Three specifications of the Cobb-Douglas functional form are reported. They differ according to whether a monthly time trend was included in the model (only in column 3) and whether interaction effects between drug class and quarter were included (only in column 3). Overall the models fit the data well with R^2 statistics of 0.60 to 0.95.

The estimated elasticities of DTCA and detailing are quite stable across model specifications. For spending on DTCA the estimated elasticity ranges from 0.096 to 0.114. All estimates are very precise with t-statistics of about 10. The results suggest that a 10% increase in DTC spending would result in an approximately 1% increase in sales, other things equal.

The case of proton pump inhibitors (PPIs) offers insights into the implications of this result. Between 1998 and 1999 PPI class sales grew from $4.2 billion to $5.7 billion, a change of nearly 36%. During the same period DTCA spending for PPI products grew from $49.7 million to $80.1 million, an increase of 60%. Using an elasticity of 0.10 based on the results reported above suggests that about 6 percentage points of the growth in PPI spending is directly attributable to DTCA. That translates into $252 million in sales or about 17% of the sales increase from 1998 to 1999. Note that the increase in PPI sales directly attributable to increased DTCA is about 8.3 times the increase in DTCA ($252 vs. $30.4 million).

For the case of nasal sprays DTC spending grew by 37% between 1998 and 1999 (from $83 to $115.2 million). The corresponding growth in sales was from $726 million to $990 million or 36%. The elasticity estimate suggests that the growth in DTC spending was responsible for a 3.7% growth in sales, or 10.3% of the total growth in sales. That amounts to about $26 million. Here the sales increase directly attributable to increased DTCA spending is only 0.8 times the DTCA increase ($26 vs. $32.2 million). Industry officials have suggested to us that their targeted changes in sales are in the range of four to five times the change in DTCA spending at the brand level (increased sales are also associated with increased production costs, sales commissions, licensing fees and general administrative costs).

The coefficient estimates for the impact of detailing on sales imply elasticity estimates of between 0.017 and 0.034. Again all three estimates are quite precisely estimated with t-statistics ranging from 4.25 to about 10. Because changes in detailing were on the order of 7% to 15% in the late 1990s and early 2000s, the impact of growth in detailing on class sales is considerably smaller than it was for drugs using DTCA as a key promotional strategy. Thus, at the entire class level, for these therapeutic classes DTCA has a larger marketing elasticity than does detailing.

Tables 4 and 5 present the product specific demand models. All product-specific models include class fixed effects. Table 4 presents results for models where a relative price measure is included as a right hand side regressor. Table 5 omits the relative price measure and instead includes quarterly dummy variables and interactions between quarter and class. The quarters are meant to account for seasonal effects and the fact that these might vary for different classes (antihistamines vs. antidepressants). All six sets of estimates presented treat detailing and DTCA as endogenous.[14] Incidentally, one finding worthy of note in the first stage regressions is that the impact of the 1997 FDA clarification on regulations governing DTCA had no significant effect on DTCA spending levels

IV estimates of the coefficient on the price variable in Table 4 are positive, significant in two of the three models, and of the wrong sign. As noted earlier, we believe the price variable is measured with error, and has no close relationship to patient copayments.

The various models in Tables 4 and 5 yield relatively consistent findings with respect to the estimates for the effect of DTCA and detailing on individual product sales. The coefficient estimates for the log of DTCA are consistently positive and quite imprecisely estimated. In five of six specifications the standard errors are larger than the estimated coefficient. In the first column of Table 5 the estimated coefficient has a t-statistic of 1.92 that is not quite significantly different from zero at conventional levels. The estimated DTCA elasticities are not consistent in magnitude across the estimated models, nor in levels vs. shares. To the extent DTCA affects class sales, one would expect a larger level elasticity (column 3) than a share elasticity (columns 1 and 2). This is not always the case. However, the Cobb Douglas model on Table 5 yields an elasticity of about 0.22, larger than the share elasticity.

The results for the impact of detailing on sales for individual drugs show coefficient estimates that are typically positive and imprecisely estimated. The first column of Table 5 reports a negative coefficient estimate for the log of detailing variable, but this coefficient is not significantly different from zero at conventional levels. Although the detailing elasticity estimates are all larger than those for DTCA, the detailing elasticity estimates never approach statistical significance.

Order of entry and its square were never found to be significantly different from zero in any of the estimated models. The magnitudes of the DTCA and detailing coefficients in the product-level models are quite sensitive to the form of the dependent variable and to the manner in which time dummies are specified. Finally, we also estimated a variant of the Cobb-Douglas model where both own DTCA and competitor DTCA levels were specified as right hand side variables. The results were not materially different from those reported in Tables 4 and 5. The time trend results for the share regressions reflect therapeutic competition in that they tend to be negative for most of the observed period as the number of competitors increases. The quantity regression reflects the growth in the class over time and this a generally positive time trend.

VII. Comments on Results

The DTCA parameter estimates we obtained at the therapeutic class level are both robust and precisely estimated. Estimates of the detailing elasticities at the therapeutic class level are also positive and significantly different from zero. They are generally smaller than the DTCA elasticities, and not as robust. In contrast, both DTCA and detailing parameter estimates for the individual product demand models are neither robust nor precisely estimated.

To simulate the overall impact of changes in DTC advertising on drug spending growth, our estimates were applied to changes in spending from 1999 to 2000 for the 25 drug classes with the highest retail sales. Drugs in these classes accounted for about 60% of the DTC advertising and about 75% of retail sales over that period. We applied our 0.10 elasticity to total DTCA spending growth for those classes that advertise and multiplied this figure by 1999 sales for those classes.[15] The absolute change in sales attributable to DTCA was then compared to the actual growth in prescription drug sales. Using this approach, we estimate that $2.6 billion or 12% of the growth in total prescription drug spending between 1999 and 2000 was attributable to DTCA. This effect translates into a yield of an additional $4.20 in sales for every dollar spent on

DTC advertising. Thus, our estimates indicate that DTCA is important, but not the primary driver of recent growth.

Despite these results, we believe it is premature to conclude that DTCA only affects class level sales, and not individual product sales. The stability of both DTCA and detailing spending is far greater at the class than at the individual product level, and thus the product level demand models may not be properly capturing the complex timing relationships between marketing efforts and measured sales, particularly because the latter involve sales to drug stores, not from drug stores to patients. However, the three-month cumulative log formulation gave similar results, even though it was less volatile than the current flow measure. The greater stability at the class level gives us some confidence in the class level results.

One potential reason for the instability of results at the product level is experimentation with DTCA by drug manufacturers. An implication is that such trial and error spending creates noise at the individual product level while there is relative stability at the class level. In addition, some of this experimentation may have failed to increase own brand sales, but still increased class demand. As a result, we view the question of the impact of DTCA spending at the individual product level as still remaining quite uncertain, and meriting further research. If our results suggesting larger class effects stand up after further research, they are consistent with the notion that DTCA leads previously untreated patients to talk to their doctors about advertised treatments and that these discussions sometimes lead to a prescription. How physicians balance their own product preferences and those of consumers is less certain.

This interpretation of our DTCA findings fits with the microeconomic evidence reported by Wosinska [2001] for cholesterol-reducing medications. She finds that DTCA, unlike detailing, affects individual drug market share only if that brand happens to have preferred status on the third party payer's formulary. It is also consistent with evidence from Ling, Berndt and Kyle [2002], who find that for the H_2-antagonists DTCA on over-the-counter (OTC) brands has a positive impact on own-brand OTC market share, but there is no significant spillover impact on same-brand Rx market share, nor does DTCA on the Rx brand impact Rx market share.

If health care were like any other commodity, we could presume that increasing utilization of pharmaceutical treatments is unequivocally beneficial. Due to the presence of insurance and asymmetric information, however, the welfare effects of DTCA are uncertain. For conditions such as depression and high cholesterol, which are believed to be under-treated in the population, increases in prescription drug treatment may have substantial benefits. There are also reasons to question, however, the appropriateness and cost-effectiveness of the treatment that results from DTCA. Further exploration of the characteristics of the patients, doctors, and treatment episodes that are influenced by DTCA is clearly needed.

Table 1: Spending on Physician-Directed Promotion and Promotion to Sales Ratios, 1996-2000

Dollars (millions)	1996	1997	1998	1999	2000
Detailing	3,010	3,365	4,057	4,320	4,803
Journal Advertising	459	510	498	470	484
Retail Value of Samples	4,904	6,047	6,602	7,230	7,954
Total Physician Promotion	8,373	9,922	11,157	12,020	13,241
Direct-to-Consumer Promotion	791	1,069	1,317	1,848	2,467
Total Promotion	9,164	10,991	12,474	13,868	15,708

Promotion to Sales Ratios	1996	1997	1998	1999	2000
Detailing	0.046	0.047	0.050	0.043	0.043
Journal Advertising	0.007	0.007	0.006	0.005	0.004
Retail Value of Samples	0.076	0.084	0.081	0.071	0.071
Total Physician Promotion	0.129	0.138	0.137	0.118	0.118
Direct-to-Consumer Promotion	0.012	0.015	0.016	0.018	0.022
Total Promotion	0.141	0.153	0.153	0.136	0.140

Sources: Physician Promotion spending data are from IMS Health, *Integrated Promotion Service,* June 2001; Sales data are from Pharmaceutical Research and Manufacturers of America, Annual Survey, 2001; Direct-to-Consumer Promotion spending data are from IMS Health and Competitive Media Reporting, June 2001.

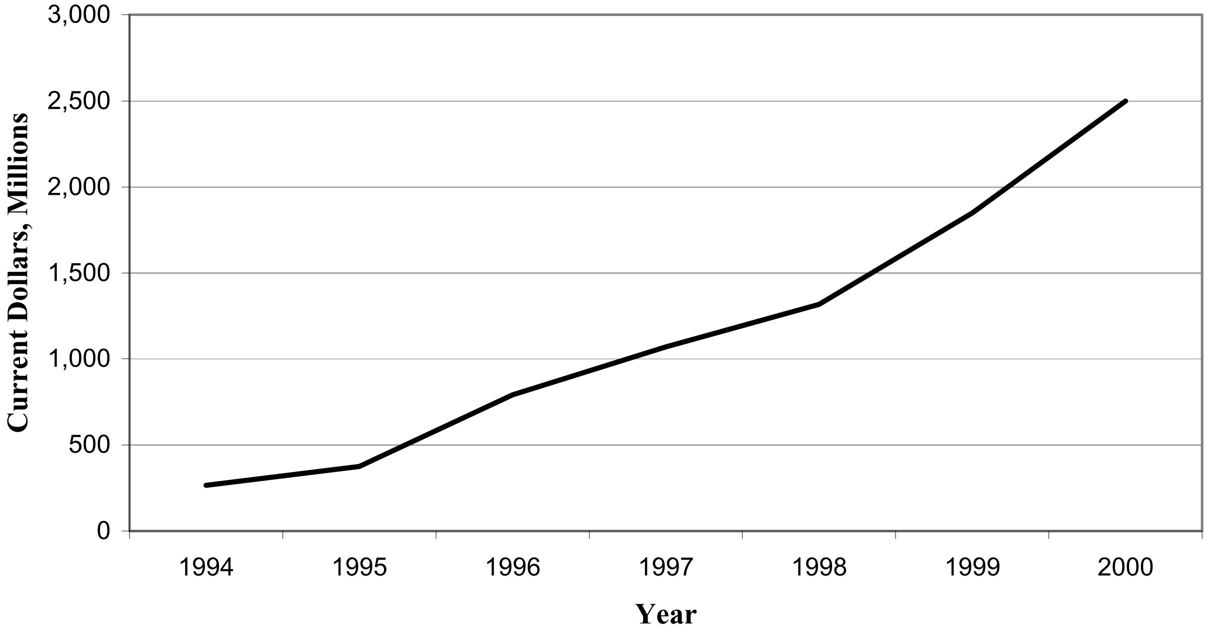
Table 2: Manufacturer, Approval Date and Promotion to Sales Ratios for Five Therapeutic Classes, 1997-1999

	Manufacturer	FDA Approval Date	3-year Detailing to Sales Ratio	3-year Sampling to Sales Ratio	Total Physician Promotion to Sales Ratio*	3-year DTC to Sales Ratio
Antidepressants						
CELEXA	Forest Labs	1998	0.31	0.21	0.52	0.00
SERZONE	Bristol Myers Squibb	1994	0.21	0.15	0.35	0.01
EFFEXOR XR	Wyeth Ayerst	1993	0.12	0.09	0.21	0.00
PAXIL	GlaxoSmithKline	1992	0.05	0.10	0.16	0.01
ZOLOFT	Pfizer	1991	0.05	0.10	0.14	0.00
PROZAC	Eli Lilly	1987	0.03	0.06	0.09	0.01
PPIs						
ACIPHEX	Eisai	1999	1.21	0.84	2.05	0.00
PREVACID	Tap Pharm	1995	0.05	0.10	0.15	0.00
PRILOSEC	Astrazeneca	1989	0.02	0.06	0.08	0.02
Antihistamines						
ASTELIN	Wallace	1996	0.49	0.19	0.68	0.00
SEMPREX-D	Celltech Pharms	1994	0.26	0.18	0.44	0.00
ALLEGRA	Aventis	1996	0.17	0.09	0.26	0.11
ZYRTEC	Pfizer	1995	0.14	0.17	0.30	0.15
CLARITIN	Schering Plough	1993	0.04	0.04	0.08	0.06
Cholesterol						
LESCOL	Novartis	1993	0.11	0.07	0.18	0.00
PRAVACHOL	Bristol Myers Squibb	1991	0.06	0.07	0.13	0.05
LIPITOR	Pfizer	1996	0.05	0.07	0.12	0.01
ZOCOR	Merck	1991	0.04	0.07	0.11	0.03
MEVACOR	Merck	1991	0.00	0.02	0.02	0.00
Nasal Sprays						
NASONEX	Schering Plough	1997	0.22	0.26	0.48	0.23
RHINOCORT	Astrazeneca	1994	0.12	0.20	0.32	0.00
NASACORT	Aventis	1991	0.11	0.37	0.47	0.09
FLONASE	GlaxoSmithKline	1994	0.06	0.14	0.20	0.12
VANCENASE	Schering Plough	Prior to 1982	0.03	0.37	0.40	0.00
BECONASE	GlaxoSmithKline	Prior to 1982	0.00	0.00	0.00	0.00

Sources: Detailing data from Scott-Levin Personal Selling Audit, 2001; Sales data from Scott-Levin, Source Prescription Audit, 2001; Sampling data from IMS Health, 2001; DTCA data from Competitive Media Reporting, Strategy Report, 2001; Manufacturer and FDA Approval Date obtained from the Food and Drug Administration's *Orange Book.*

* Total Physician Promotion includes detailing and retail value of free samples. It does not include journal advertising.

Figure 1: Trend in Direct-to-Consumer Advertising Spending, 1994-2000



Source: IMS Health and Competitive Media Reporting, Inc.

Figure 2: Multi-Tier Demand Structure

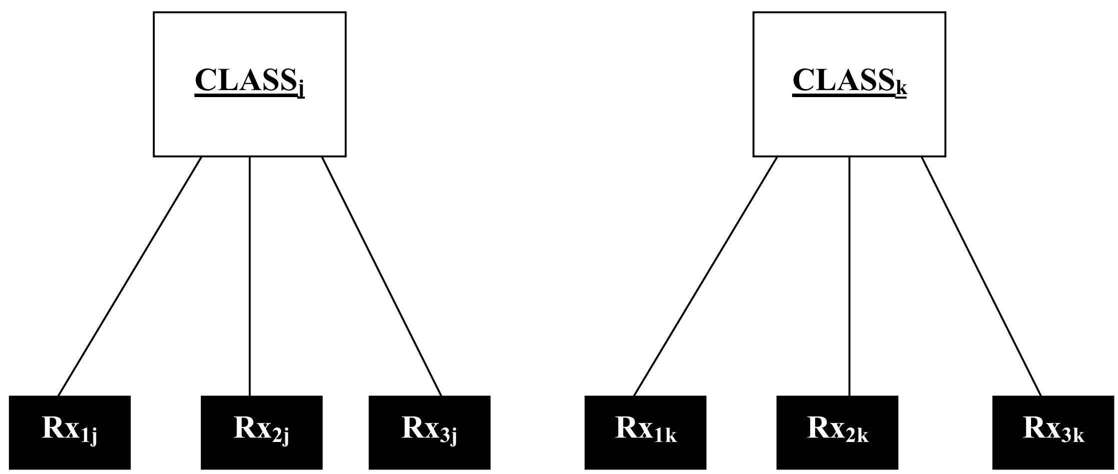


Table 3: Drug Class Demand Models

	Dependent Variables		
	ln Q	ln Q	ln Q
Class DTC*	0.114 (0.01)	0.099 (0.01)	0.096 (0.009)
Class Detail*	0.017 (0.004)	0.034 (0.003)	0.031 (0.003)
Quarter Dummies	Included	Included	Included
Class Dummies	Included	No	No
Interaction	Included	No	No
Month	No	No	Included
$Month^2$	No	No	Included
Constant	10.02 (0.18)	9.92 (0.19)	9.89 (0.20)
R^2	0.95	0.60	0.62
Equation F	280.0	56.0	48.87

*Endogenous, IV estimated

Note: Robust SE in parentheses

Table 4: Individual Product Demand Models With Prices

	Dependent Variables		
	Dollar Share	Ln [(Q Share)/(1-Q Share)]	ln Q
Constant	-0.281 (0.88)	-9.971 (4.66)	1.544 (4.23)
ln DTCA*	0.025 (0.03)	0.091 (0.11)	0.071 (0.11)
ln Det*	0.004 (0.14)	0.690 (0.698)	0.730 (0.63)
Order entry	0.127 (0.69)	0.619 (0.49)	0.615 (0.49)
$(\text{Order entry})^2$	-0.017 (0.009)	-0.087 (0.09)	-0.089 (0.09)
$\ln (P_i/P_{others})$	0.129 (0.07)	1.120 (0.41)	1.108 (0.39)
Class dummies	Included	Included	Included
Month	-0.0004 (0.03)	-0.171 (0.01)	0.042 (0.02)
Month^2	0.720 (0.88)	0.0022 (0.0003)	-0.0007 (0.0004)
R^2	0.54	0.65	0.69
Equation F	16.51	54.99	34.97

*Endogenous, IV estimated

Note: Robust SE in parentheses

Table 5: Individual Product Demand Models With Price Excluded As Regressor

	Dependent Variables		
	Dollar Share	ln [(Q Share)/(1-Q Share)]	ln Q
Constant	1.746 (1.29)	-9.771 (10.58)	4.413 (10.79)
ln DTCA*	0.077 (0.04)	0.167 (0.23)	0.216 (0.24)
ln Det*	-0.254 (0.18)	0.77 (1.43)	0.443 (1.46)
Order entry	0.100 (0.06)	0.269 (0.62)	0.313 (0.61)
$(\text{Order entry})^2$	-0.011 (0.01)	-0.067 (0.10)	-0.071 (0.10)
Class dummies	Included	Included	Included
Quarter dummies	Included	Included	Included
Interaction	Included	Included	Included
Month	-0.007 (0.004)	-0.181 (0.04)	0.026 (0.03)
Month^2	0.0001 (0.0001)	0.002 (0.0009)	-0.0003 (0.001)
R^2	0.37	0.47	0.52
Equation F	24.42	51.86	17.96

*Endogenous, IV estimated

Note: Robust SE in parentheses

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ENDNOTES

[1] These and other quotes are shamelessly lifted from Carlton-Perloff [1994], chapter 15, Advertising and Disclosure, pp. 596-629.

[2] As quoted in the Boston Globe (Mishra [2002]). Words in parentheses added for clarification.

[3] However, prior to the 1938 FDA prescription-only legislation and the 1951 Humphrey-Durham Amendment to the Federal Food, Drug and Cosmetic Act that established physicians as “learned intermediaries” and made many drugs available only with a physician’s prescription, DTCA dominated drug advertising. Temin [1980, pp. 82-87] estimates that in 1930, 90% of drug advertising expenditures occurred in newspapers and popular magazines, only 2% in technical journals, and only 3% involved detailing, samples and other.

[4] For an historical account of DTCA controversies, see Masson [1991].

[5] On this, also see Ziegler, Lew and Singer [1995].

[6] Twenty-five years of experience in modeling the impacts of detailing on sales, and on optimizing sales force size and targets, is summarized in Sinha and Zoltners [2001]. A classic study of detailing is that by Lodish et al. [1988].

[7] These and other quotes are shamelessly lifted from Carlton-Perloff [1994], chapter 15, Advertising and Disclosure, pp. 596-629.

[8] Carlton-Perloff [1994], p. 603.

[9] Carlton-Perloff [1994], p. 625.

[10] For empirical evidence on consumers' search costs for acute vs. chronic medications, and impacts on retail pricing of drugs, see Sorenson [2000].

[11] Also see Scherer [2000].

[12] Industry officials tell us that absolute levels of DTCA spending are likely overstated because CMR estimates DTCA spending using “list” rather than actual transaction prices. Because of the large amount of advertising services pharmaceutical firms purchase, they typically obtain substantial discounts off list prices. These industry officials suggest that the DTCA estimates by CMR are reasonably reliable estimates of relative DTCA across drugs.

[13] We also estimate a variant of the strict two stage budgeting model where we allow both class level DTCA and own DTCA to affect the demand for a particular drug.

[14] First stage estimates are available from the authors upon request.

[15] We also attempted to simulate the impact of DTC advertising class by class as would be appropriate given the underlying economic model, but were forced by this method to exclude a number of classes with positive DTC spending because of sales or DTC spending reductions from 1999 to 2000, or because DTC spending was zero in either 1999 or 2000. Such exclusions inflated our simulated result, yielding an estimate that 22% of prescription drug sales growth was attributable to DTC spending increases. The simulation we report in the text (a 12% growth in sales attributable to DTC) aggregates sales and DTC advertising across classes to smooth out these anomalies. While this approach may have some downward bias due to the way DTC spending is distributed across classes with different levels of dollar sales, we believe that this estimate is more defensible because it includes all of our data from the 25 classes studied.

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